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Research on signal modulation identification method based on residual neural network

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Abstract: Aiming at the problems of large number of parameters, high complexity and low recognition accuracy of the current modulation recognition model based on high-performance neural network, a lightweight signal modulation recognition algorithm based on residual neural network (ResNet) is proposed. Firstly, the ResNet network model is built, which contains two residual units and three fully connected layers. Secondly, the pruning method of network slimming is introduced to compress the neural network model without affecting the recognition accuracy. Finally, the model was trained using modulated signal samples for the RaidoML2016.10a international standard dataset. The experimental results show that the recognition accuracy of the pruning ResNet modulation recognition algorithm can reach 95% under the condition of 12dB signal-to-noise ratio, and the number of model parameters is only 5.7×104.

Keywords: Deep learning; Modulation recognition; Residual network; Lightweight.

1. Introduction

Signal modulation identification is a technique to obtain [1] the modulation mode of a signal by analyzing and processing the received signal in the case of unknown information or lack of a priori information. Modulation recognition has been widely used in both military and civilian fields, such as electronic countermeasures and spectrum detection. Deep learning based modulation recognition methods have [2] greater advantages in automatic feature extraction, robustness, etc., but there are still shortcomings such as high data requirements and high model complexity, which greatly limit its application on the ground, so there is a need to study and implement lightweight modulation recognition algorithms.

In 2016, O'Shea et al [3] used convolutional neural network (CNN) to classify radio signals, and its modulation recognition model structure contains two convolutional layers and two pooling layers, and the experimental results show that the recognition accuracy of CNN is 73% in the modulation recognition task. In order to solve the defects such as gradient dispersion of convolutional neural networks, in 2018, the authors in the literature [4] proposed a modulation recognition method for radio signals based on Deep Residual Neural Network, which introduces multiple Residual Blocks (Residual) structures based on the use of convolutional neural networks in the literature [3] to improve the model. Blocks) structure to improve the model recognition accuracy and generalization ability, the experimental results show that the number of parameters of the modulation recognition model based on residual neural network is 2.3×105, and the recognition accuracy is up to 94% when the training dataset is 740,000.In 2020, S. Hu et al [5] proposed a classifier based on deep neural networks (DNNs) to classify the signal modulation recognition. In the above literature study, it is found that even a simple CNN neural network modulation recognition model has a parameter count of up to 2.8×106 and requires 40 minutes of training, which is unaffordable in a communication environment where the actual resource conditions are limited and require constant training and adaptation to different conditions. Therefore, studying modulation recognition methods under resource-constrained conditions can better adapt to the needs in real scenarios, improve the performance of modulation recognition and reduce resource consumption. These methods usually include the use of lightweight neural network structures, compression techniques, pruning techniques, quantization techniques, and so on. ; In 2021, S. Zhang et al [6] proposed a modulated signal recognition model based on a lightweight deep learning network.In 2022, Satish et al [7] proposed a lightweight deep learning approach for signal modulation classification task. The original network is first trained and then the size of the network is reduced by iterative pruning and three-weight quantization and deployed on the hardware platform ZU111 for real-time signal modulation recognition. In the literature [8] the authors proposed a modulation identification method based on neural network architecture search and accelerated the network model using partial channel pruning.2022, Min Zhang et al [9] proposed a neural network identification method for radar signals and pruned and fine-tuned the network connections and weights in the neural network to achieve lightweight signal modulation classification.

In order to improve the accuracy of the deep learning-based signal modulation recognition algorithm, reduce the complexity of the network and the number of parameters, and improve the feasibility of the algorithm [8] to port small embedded devices. In this paper, we build a ResNet-based modulation recognition network model and prune the network using the pruning technique in network lightweighting to reduce the computation and complexity of the model.

1.1. Signal modulation mode identification process

Currently, modulation recognition algorithms can be divided into two categories from the perspective of whether or not they utilize deep learning algorithms: classical modulation algorithms, and intelligent modulation recognition algorithms based on deep learning. Classical modulation recognition algorithms are divided into two main categories: decision-theory-based maximum likelihood hypothesis testing methods and feature extraction-based pattern recognition algorithms [10]. Decision-theoretic likelihood-based testing methods are sensitive to non-Gaussian noise and require manual adjustment of the threshold, which is not effective in practical engineering applications. Statistical pattern recognition algorithms based on feature extraction require a large amount of computational resources, resulting in reduced recognition performance and poor real-time performance. Deep learning-based modulation recognition methods do not require data preprocessing and feature extraction steps, the data can be directly input into the network, the middle layer of the network automatically mines the data feature information. Therefore, compared with the traditional modulation recognition method, deep learning based modulation recognition method [10] has the advantages of automatic feature extraction, robustness, adaptability and so on, which is one of the important research directions of modulation recognition in the future radio communication field.

Deep learning based modulation identification methods [11] refer to the automatic classification and identification of digital modulated signals using deep learning algorithms such as Deep Neural Networks (DNNs) or Convolutional Neural Networks (CNNs) [12]. Applications in the field of wireless communication include signal classification, channel estimation, adaptive modulation, and automatic coding. A multi-layer neural network model is used to learn the features of the input signals and extract more abstract and advanced features, so as to realize the modeling of complex mapping relationships of the input signals, and then to realize various wireless communication tasks. When dealing with wireless communication signals, the time-domain or frequency-domain representations of the signals can be used as input data, and the model can be trained to realize tasks such as classification, prediction, or generation of the input data.

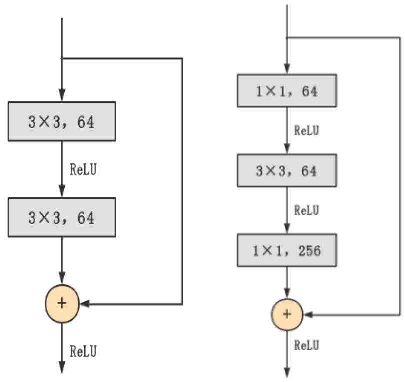
2. ResNet-based modulation recognition algorithm

2.1. Principles of Residual Neural Network (ResNet)

Convolutional neural network, as a basic model of deep learning, has powerful feature extraction and classification capabilities. However, with the deepening of related research, it is found that deep learning defects, such as gradient vanishing and gradient explosion, appear with the increase of network depth, which makes the network difficult to train and optimize. Therefore, how to solve the gradient dispersion problem while ensuring the increase of model depth has become an important research direction in the field of deep learning [1].

In order to overcome these problems, residual neural networks have emerged. Kaiming He et al [13] from Microsoft Research Asia proposed ResNet in 2015, which introduced residual block and shortcut connection. The residual block contains two convolutional layers and a jump connection, allowing the network to learn residual information at a deeper level. The residual block divides the mode into two paths, the right path is called ship connection, the principle is that the input x reaches the output y directly along the ship connection, preserving the original input x value; while the middle path is a two convolutional layers, the principle is that the input x is passed through the weight matrix W and bias coefficient b inside the convolutional layer, and then through the activation function F to get F(x), the output of the residual block can be expressed as H(x) = F(x) + x. F(x) in this equation is called residual because it represents the difference between the output H(X) and the input x. As residual learning, residual learning makes deep neural network easier to train. multiple convolutional layers and jump connections. By superimposing multiple layers of residual blocks, the ResNet network can therefore realize a very deep network structure, which effectively mitigates the gradient vanishing and gradient explosion problems, and thus improves the performance and training efficiency of the network.

ResNet's residual module has two main forms, as shown in Fig. 1. Where (a) is the basic form and (b) is the bottleneck form. In the bottleneck form, a 1 × 1 convolutional kernel is used to reduce the computational complexity and also to improve the nonlinearity of the model [14]. This idea draws on criterion 3 in the Inception v3 model proposed by Szegedy et al [15], which states that after spatial aggregation, the downscaled features maintain the integrity of the information. In this way, the residual module in the form of a bottleneck is better able to handle high-dimensional features and can improve the efficiency of the model.



(a) basic form (b) Forms of bottlenecks

Fig. 1 ResNet residual block form

2.2. ResNet algorithm model

Table 1. ResNet-based modulation recognition model

Layer	output
Input	2×128
Residual stack Maxpool	32×64 32×32
Residual stack Maxpool	32×32 32×16
FC/SeLu	32
FC/SeLu	16
FC/Softmax	11

In this paper, we build the improved ResNet neural network architecture suitable for the modulation recognition task, as shown in Fig. 2. The network model is constructed on the dataset RaidoML2016.10a containing 11 modulation recognition signals commonly used in communication signals, and the input to the network is a sequence of IQ samples of size (2, 128), which does not require human pre-extraction of features [1].The internal structure of the ResNet consists of Residual Units and Residual Stacks, and the structure is shown in Fig. 3.The ResNet Neural network consists of two Residual Stack units, the structure is shown in Fig. (a), a

Residual Stack unit contains two residual modules, a Residual Unit residual module consists of three convolutional layers, which contains three layers, the structure is shown in Fig. (b), the overall number of layers of the network and the structure of the output is shown in Table 1.

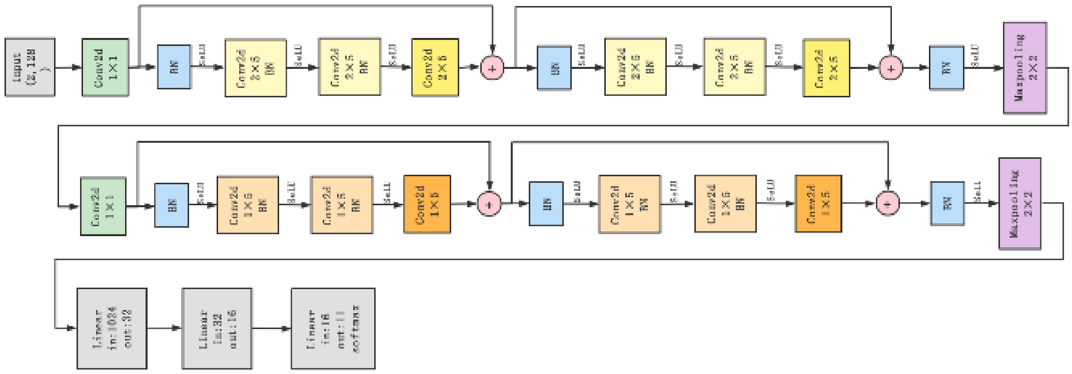
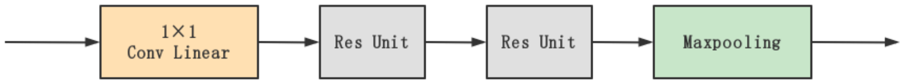
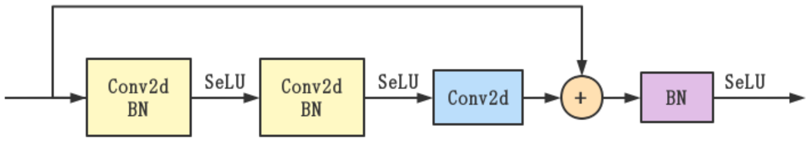


Fig. 2 ResNet signal modulation recognition network structure



(a) Residual Stack



(b)Residual Unit

Fig. 3 Internal structure of ResNet

Inside the Residual Unit residual module, a normalization layer (BN) is used after each convolutional layer to correct the data distribution and improve the network training speed. In addition, considering that the signal feature distribution is different from the image pixel values, and the feature values are both positive and negative, the SeLU function is used after the normalization layer instead of the traditional activation function ReLU to increase the nonlinearity of the model, while retaining the negative features of the signal as much as possible [1]. Each Residual Stack unit includes a convolution kernel of size (1, 1), which is used to do the computation in channel dimension, in the first Residual Stack unit, due to the input data format of (2, 128) for the two IQ data, set the size of the convolution kernel inside the residual module of the Residual Unit are (2, 5). The number of convolution kernels is 32, and after a maxpool of size (2, 2) the dimension becomes (1, 64), at this time the dimension of the convolution kernels inside the Residual Unit residual module in the next Residual Stack unit should not be larger than the input data, so the size of the convolution kernels inside the second Residual Stack unit are both (1, 5), and the number of convolution kernels is 32, which facilitates the input data format of (2, 128) two-way IQ data. The number of convolutional kernels is 32, which is favorable to reduce the number of neural network parameters. Finally, three fully connected layers are used to extract the joint information between different feature channels and used for classification, in which the activation function also uses SeLU instead of the traditional activation function ReLU, and the last fully connected layer adopts the Softmax function, which outputs the probability of different samples corresponding to each modulation category.

3. Model pruning

3.1. The principle of pruning

Neural network pruning is a technique to reduce unnecessary parameters in the neural network, the main idea is to achieve the compression and sparsification of the parameters in the network by setting some parameters in the network to zero, which can effectively reduce the amount of computation and storage space of the model and improve the computational efficiency and generalization performance of the model.

In recent years, with the development of deep learning techniques, automated data-based pruning methods have gained much attention. One such method is network refinement, which is achieved by continuously removing weights smaller than a certain threshold during training. Another approach is to use iterative pruning, where a certain number of neurons and connections are removed in each iteration cycle and the model is then retrained. This approach allows the model to be dynamically pruned during model training, allowing the size of the model to be gradually reduced as training [2] proceeds. There are also compression-based methods, such as structured pruning, that reduce the number of parameters in the model by cutting down the network structure. Among them, common methods include channel pruning and layer pruning. Channel pruning involves removing entire channels from the network, while layer pruning involves removing entire layers from the network. These methods can be used to determine which channels or layers can be pruned by calculating the importance of each channel or layer for optimal network compression.

3.2. Introduction to the Pruning Algorithm

Liu et al [16] proposed Network Slimming pruning method in 2017, Network Slimming can prune the weights in the convolutional kernel to further compress the number of parameters of the model. The main idea is to constrain the weights in the convolutional kernel by L1 regularization, making some unimportant weights become small or zero, so as to prune the corresponding channel or convolutional kernel. During the training process, Network Slimming controls the sparsity of the weights by dynamically updating the L1 regularization coefficients.

1)Specifically, the pruning principle of Network Slimming can be summarized in the following steps:

2)Constrain the weights in the convolutional kernel by L1 regularization during model training;

3)Calculate the number of channels or convolution kernels to be retained according to the size of the weights after constraints;

4)The channels or convolution kernels with zero weight values after constraints are directly pruned away, and these parameters are not updated again in the subsequent training;

After pruning, retrain the model by fine-tuning to recover the accuracy.

In this way, Network Slimming can compress the number of parameters of the model to 10%~40% of the original one without reducing the accuracy.Network Slimming can be performed in different dimensions, including kernel dimension, channel dimension and layer dimension. In this paper, we choose to perform the pruning in channel dimension, due to the fact that in the ResNet network structure, a data normalization layer (BatchNormalization) is added after each convolutional layer, BN:

$$\mathrm{BN} = \gamma \widehat{X}_1 + \beta \tag{1}$$

$\widehat{X}_1$ is the input data after normalization, the parameter γ can be used as a weight to measure the importance of the channel. In 2D convolution, the different Normalization methods are shown in Fig. 4, from which it can be seen that the BN itself is performed in channel dimension, i.e., each γ value corresponds to a channel. Therefore, this method is chosen not only to facilitate the incorporation into the existing network architecture, but also to minimize the loss of accuracy.

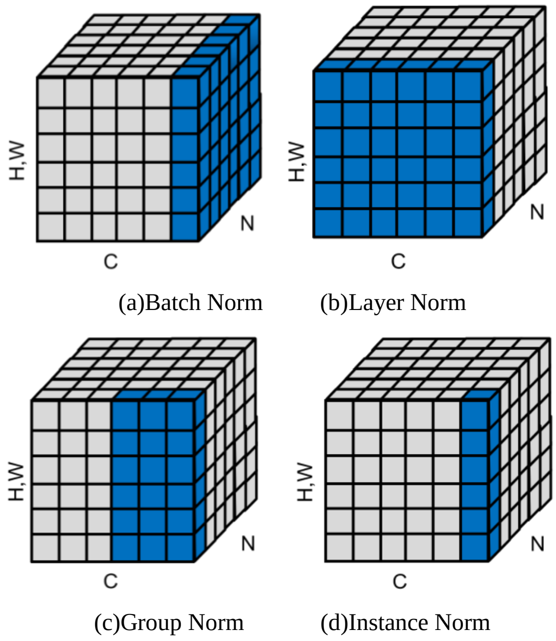


Fig. 4 Different ways of Normalization

The pruning of the already trained original model ResNet is performed, the pruning ratio is based on the numerical size of all the LAYERS, if all the parameters γ of a BN layer are particularly large, then this layer channel remains unchanged, on the contrary, only one channel is left. Before pruning, all layers in the network are first traversed to obtain the parameters γ of all BN layers and sort them according to their size. The threshold value of γ is determined according to the per cent pruning ratio, and γ smaller than the threshold value is set to 0. Subsequently, according to the number of retained channels, a new model with the same structure as the original model but with different dimensions of each layer is constructed, and the corresponding weights are assigned to the convolutional, BN, and fully-connected layers of the new model, respectively. Finally, the pruned model is trained.

4. Experimental results and performance analysis

4.1. Training dataset

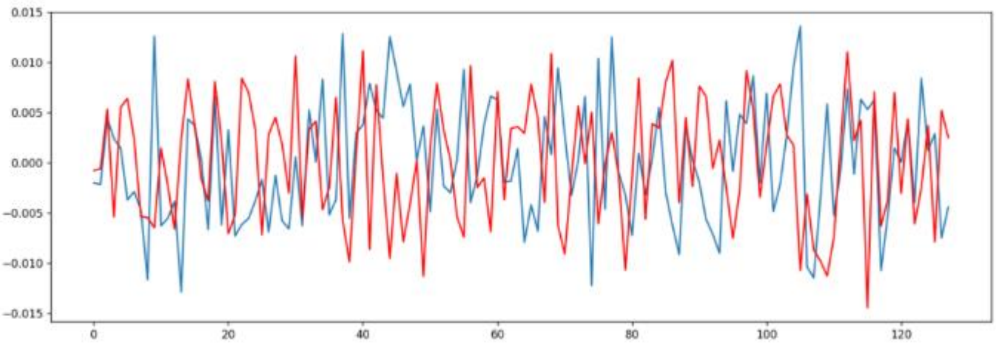


Fig. 5 Schematic diagram of extracted samples from the RaidoML 2016.10a dataset

The RaidoML2016.10a dataset is an international standard dataset for modulation identification, published by Timothy O'Shea [3] et al. in 2016. The dataset contains eight digital modulation signal types and three analog modulation [17] signal types for analog radio signals at 20 signal-to-noise level levels. Each modulation scheme has one SNR level per

2 dB in the range of -20 to 18 dB, for a total of 20 SNR levels. Each SNR level contains 1,000 samples of IQ data for a total of 220,000 samples. This dataset is characterized by a large amount of noise, interference and frequency bias, which is closer to the real radio signal. Therefore, this dataset is widely used in research in the field of modulation identification and is considered one of the benchmark datasets for evaluating new algorithms. The effect of observing the data with randomly selected samples from the RaidoML2016.10a dataset is shown in Fig. 5.

4.2. Evaluation indicators

In deep learning, commonly used loss functions include Mean Squared Error (MSE) and Cross Entropy [14]. In the signal modulation recognition problem, the cross-entropy loss is usually used to measure the difference between the network's recognition results and the actual modulation method. This loss function assigns different weights to different output categories, which effectively improves the classification performance of the network. The cross-entropy loss function can be expressed as:

$$\mathrm{Loss}(\mathrm{Network}(y^i,\theta),\mathrm{Mod}_j^i) = -\frac{1}{N}\sum_{i=1}^{K}\sum_{j=1}^{L}\mathrm{Mod}_j^i \log(\mathrm{Network}(y^i,\theta)) \quad (2)$$

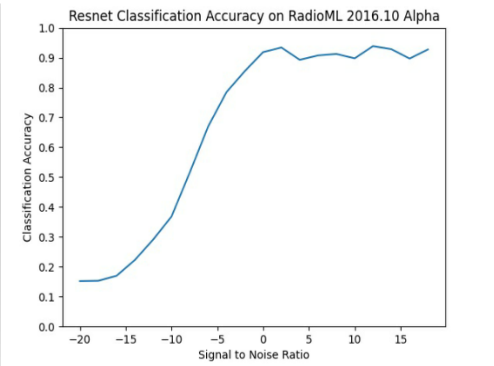
In Equation (2), N is the training samples, and the function Network is the prediction result of yi samples obtained after the processing of the neural network parameters. The network recognition accuracy (Accuracy) is calculated as follows, where denotes the true label value corresponding to the ith sample data.

$$\mathrm{Accuracy} = \frac{\sum_{i=1}^{N} g(x_i,\mathrm{Network}(y^i,\theta))}{N} \times 100\% \cdot \quad (3)$$

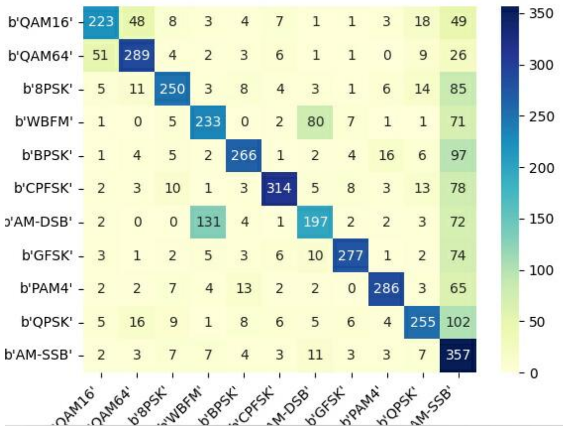
$$g(x_i,\mathrm{Network}(y^i,\theta)) = \begin{cases} 1, x_i = \mathrm{Network}(y^i,\theta) \\ 0, x_i \neq \mathrm{Network}(y^i,\theta) \end{cases} \quad (4)$$

4.3. Analysis of ResNet training results

The ResNet-based modulation recognition network was built using Pytorch in a Python 3.8 environment with a hardware platform using a Windows 10 operating system, an Intel i7 processor, and an NVIDIA GeForce MX230 graphics card. The RaidoML 2016.10a dataset was used for model training, and the random division into training and test sets was performed within the dataset in the ratio of 8:2 [15]. The learning rate of the residual neural network model was configured as 0.001, the network parameters were updated using the Adam optimizer, the training was optimized using the cross-entropy loss function, and when the iterative updating of the network related parameters was stopped, the trained model was used to identify signals from multiple modulation modes. The training results are shown in Fig. 6.



(a) Variation curve of recognition accuracy with signal-to-noise ratio



(b) Confusion Matrix for Recognition Results

Fig. 6 ResNet model training results

As can be seen from Fig. (a), there is a positive correlation between the recognition accuracy of the model and the signal-to-noise ratio under different signal-to-noise ratio conditions, i.e., the higher the signal-to-noise ratio, the higher the overall recognition accuracy. In the case of a low signal-to-noise ratio (-20dB to -15dB), the model accuracy is low; however, in the range of signal-to-noise ratio from -15dB to 0dB, the model accuracy is substantially improved and can reach 93%. In addition, when the signal-to-noise ratio is above 0dB, the recognition accuracy of the model is high, and the accuracy curve of the model basically tends to be stable, and when the signal-to-noise ratio is 12dB, the recognition accuracy of the model can reach 95%.

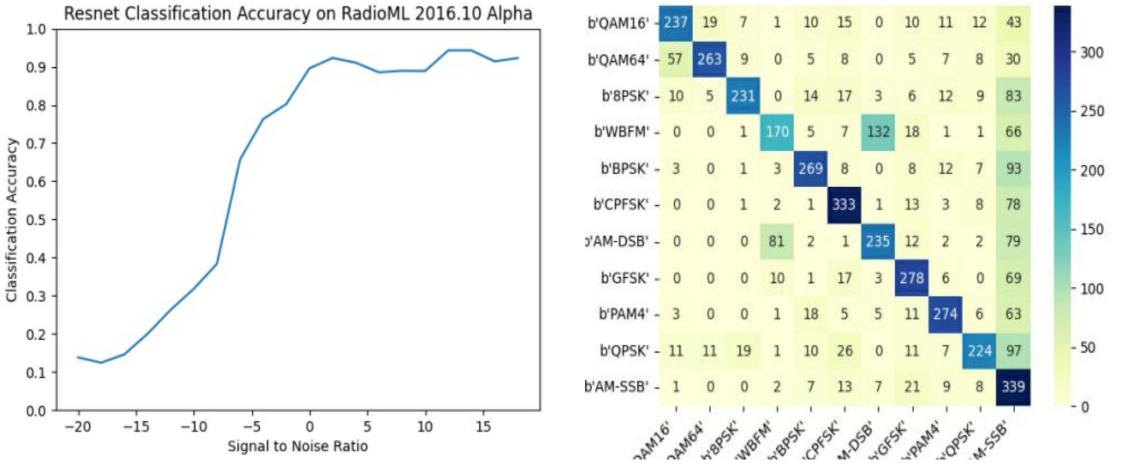
Figure (b) shows the confusion matrix of the model recognition results, which is used to show the relationship between different modulation modes and recognition accuracy under different signal-to-noise ratios. The horizontal coordinate of the confusion matrix indicates the real label of the modulated signal, and the vertical coordinate indicates the result label predicted by the model. The darker the color of the confusion matrix on the diagonal line, the higher the recognition accuracy of the signals on the diagonal line, and the darker the color on the off-diagonal line indicates that the recognition of this type of signals is easy to be confused with other signals. The confusion matrix shows that WB-FM signals are easily confused with AM-DSB signals.

4.4. Analysis of model training results under different pruning rates

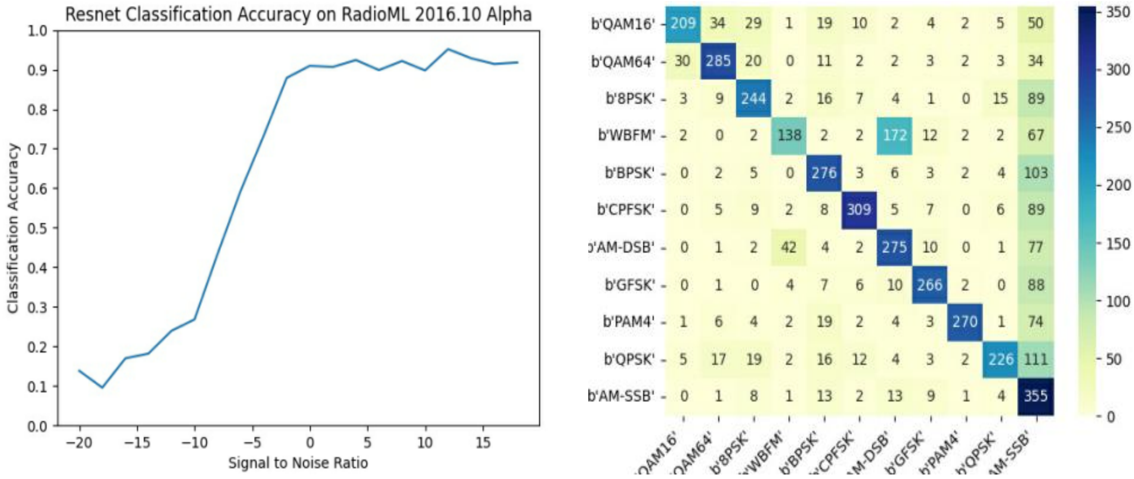
After initializing the training of the convolutional neural network, the trained network is pruned using Network Slimming pruning method, and relevant experiments are conducted for different cases of pruning ratio. As shown in Figure 7, the results of model accuracy and confusion matrix comparison under different four pruning rates are given. It is clear from the figure that as the pruning rate rises, there is a small improvement in the recognition accuracy part, but in most cases there is a partial loss of accuracy.

Analyzing the confusion matrices obtained by training the model with different pruning ratios in Fig. 11, it can be seen that at pruning ratios of 0.4 and 0.5, pruning has a small increase in the model recognition accuracy, and only produces a small amount of confusion in the recognition of WB-FM signals versus AM-DSB signals; when the pruning ratio is increased to 0.55, the model produces a small amount of confusion in the recognition of QAM16 signals versus

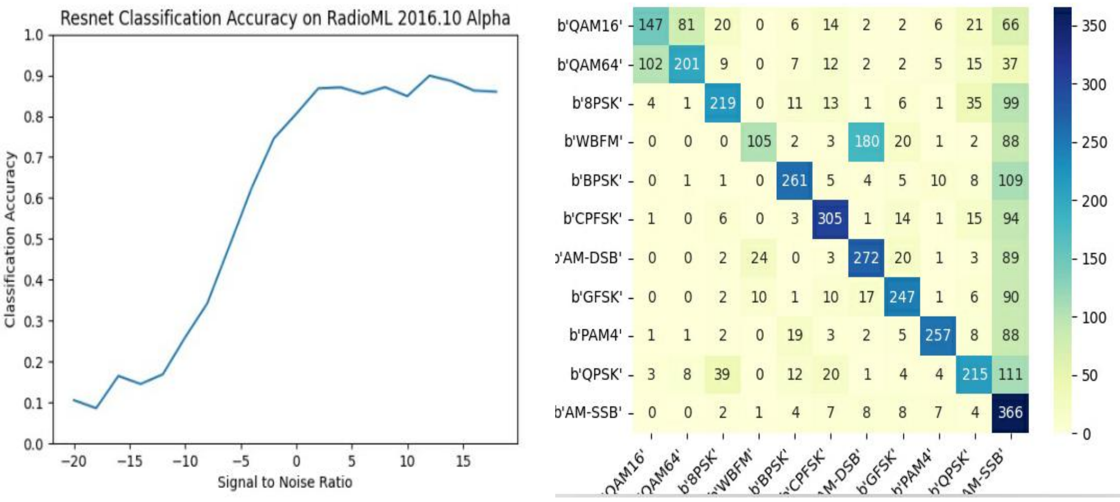
QAM64 signals, WB-FM signals versus AM-DSB signals; when the pruning ratio is 0.65, the model has low accuracy in recognizing QAM16 signals and is prone to confusion in recognizing QAM64 signals and AM-DSB signals.



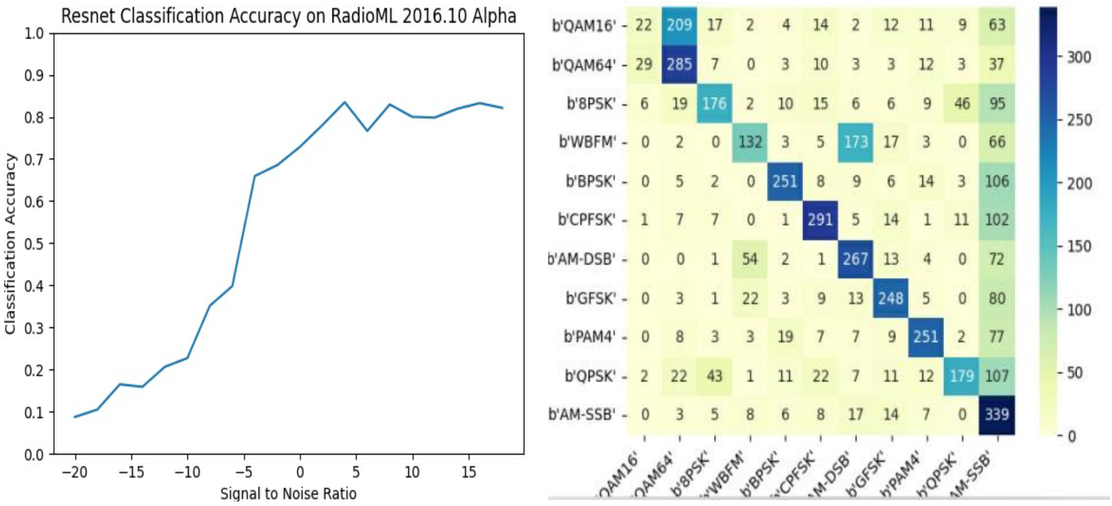
(a) Model recognition performance with a pruning ratio of 0.4



(b) Model recognition performance with a pruning ratio of 0.5



(c) Model recognition performance with a pruning ratio of 0.55



(d) Model recognition performance with a pruning ratio of 0.65

Fig. 7 Comparison of performance at different pruning rates Comparison

After the pruning experiment, the specific values of the network recognition accuracy and the reduction of network parameters can be seen in Table 2, which mainly records the signal recognition accuracy and the reduction of the convolutional layer parameters of the ResNet-based modulation recognition network model after different ratios of pruning, and it can be seen through the comparison of the data in the table that the network pruning method can improve the performance by a small margin within a certain ratio. For example, the highest recognition accuracy of 95.30% is achieved when the pruning rate is 0.4, and the highest recognition accuracy of 95.21% is achieved when the pruning rate is 0.5. However, as the pruning rate increases, although it reduces more parameters and reduces the overall number of parameters in the network, the impact on the recognition accuracy of the network also increases, and the recognition accuracy of the network starts to decrease when the pruning rate exceeds 0.55, with the highest recognition accuracy of the model being 91.45%, and the highest recognition accuracy of the model decreases to 83.86% when the pruning rate reaches 0.65. It can be seen that for the residual network, the parameters of the model are more redundant and the effect of pruning is more obvious.

Table 2. Comparison of the number of model parameters and accuracy under different pruning rates

ResNet Modulation identification model		
Pruning ratio	Parameters	Accuracy
0	113645	95.12
0.4	68187	95.30
0.5	56823	95.21
0.55	51141	91.45
0.65	39776	83.86

Build the CNN modulation based recognition network and ResNet modulation based recognition network mentioned in the literature [3] and train them using the radio signal dataset, respectively, and get the final model parametric quantities and recognition accuracy results to compare with the model mentioned in this paper, and the results are shown in Fig. 8.

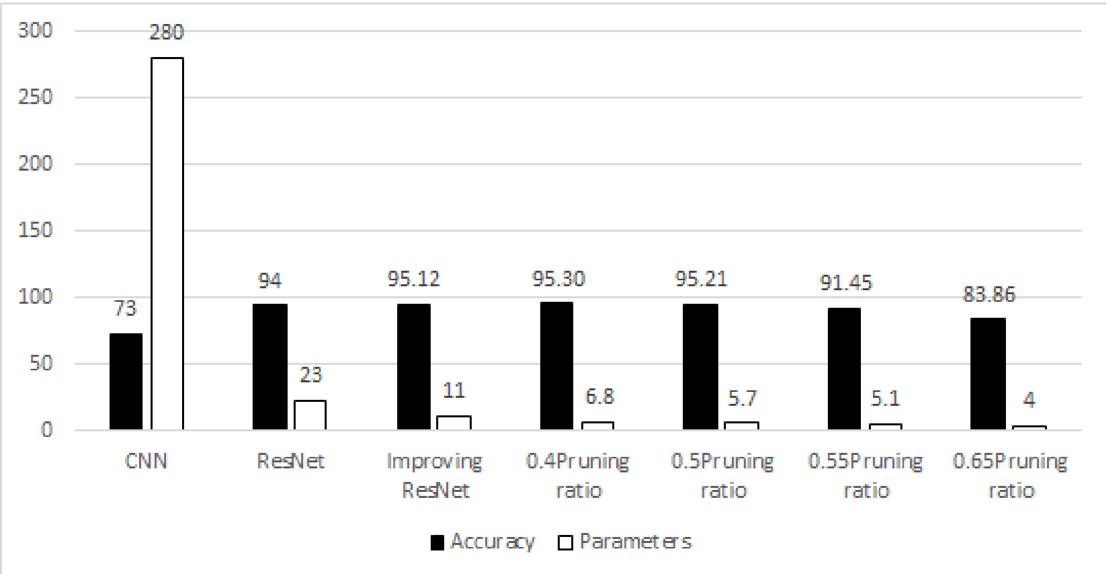


Fig. 8 Recognition accuracy of different models vs. parameters

From the comparison results, it can be seen that the ResNet modulated recognition network built in this paper has superior recognition performance on the RaidoML2016.10a dataset. Compared with the CNN-based convolutional neural network modulation recognition algorithm, the recognition accuracy is 22% higher and the amount of network parameters is reduced by dozens of times; compared with the original ResNet-based deep residual network modulation recognition algorithm, the amount of parameters is reduced to 5.7 × 104 while ensuring that the recognition accuracy is unaffected, which increases the possibility of porting to embedded devices.

5. Concluding remarks

Aiming at the low recognition accuracy of traditional signal modulation recognition methods, and the high complexity of the network of deep learning-based modulation recognition methods, the number of parameters is large, and it is difficult to be deployed in small devices, this paper builds a signal modulation recognition network based on ResNet, and compresses the network by using the method of channel pruning. Experimental results show that in the signal-to-noise ratio is greater than 0dB conditions, this paper builds the ResNet model recognition accuracy of up to 90% or more, the highest recognition rate can reach 95%, and in the case of recognition accuracy will not affect the model parameter quantity reduced to 5.7 × 104, in recognition performance, network complexity, etc., is better than the traditional method. However, the algorithm still has the following areas that need to be improved: ① In order to further improve the recognition rate at low signal-to-noise ratios, in the future, we can consider noise reduction of the signal at the input of the deep learning network first. ② The algorithm has been validated at the theoretical level, and the next step can be to deploy the algorithm on hardware devices and test its performance in mobile environments.

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